

Examining Forgetting in **Continual Pre-training** of Aligned Large Language Models

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Abstract

Recent advances in Large Language Models (LLMs) have exhibited remarkable proficiency across various tasks. Given the potent applications of LLMs in numerous fields, there has been a surge in LLM development. In developing LLMs, a common practice involves continual pre-training on previously fine-tuned models. However, this can lead to catastrophic forgetting. In our work, we investigate the phenomenon of forgetting that occurs during continual pre-training on an existing fine-tuned LLM. We evaluate the impact of continuous pre-training on the fine-tuned LLM across various dimensions, including output format, knowledge, and reliability. Experiment results highlight the non-trivial challenge of addressing catastrophic forgetting during continual pre-training, especially the repetition issue.

1 Introduction

Large Language Models (LLMs) have demonstrated impressive performance across various tasks (Brown et al., 2020). There is an increasing trend of releasing pre-trained LLMs and fine-tuned variants (Touvron et al., 2023a,b). Many of these fine-tuned variants aim to augment the knowledge or linguistic capabilities of the existing LLM (Roziere et al., 2023; Cui et al., 2023).

We have noticed that many advancements in fine-tuned variants adhere to a conventional procedure consisting of two key steps: 1. Conduct further continual pre-training on an existing LLM. 2. Carry out subsequent alignment operations, such as Supervised Fine-Tuning (SFT) and Reinforcement Learning from Human Feedback (RLHF), on the model obtained in Step 1. Among these fine-tuned variants, many developments perform further continual pre-training on existing fine-tuned LLMs (Cui et al., 2023; Lin and Chen, 2023).

Previous studies have demonstrated that continual pre-training can significantly improve the

model’s ability to understand and generate specific content (Gupta et al., 2023). However, continual pre-training could lead to catastrophic forgetting (French, 1999), and limited research has explored the abilities forgotten during pre-training on an existing fine-tuned LLM.

Some works have studied continual learning for language models. (Qin et al., 2022) focused on efficient lifelong pre-training on pre-trained language models for emerging data. (Ke et al., 2022) proposed a continual domain-adaptive pre-training method on a masked language model. (Song et al., 2023) introduced continual parameter-efficient tuning for the ongoing adaptation of LLMs to continual tasks. (Xie et al., 2023) investigate an alternative approach to continual pre-training for developing domain-specific LLMs. (Qi et al., 2023) suggests that fine-tuning compromises the safety alignment of LLMs. (Zhai et al., 2023) evaluates the forgetting in fine-tuned multimodal LLMs.

Our work examines the forgetting occurrence during continual pre-training on an existing fine-tuned LLM. Our paper primarily focuses on continual pre-training using the Traditional Chinese corpus. We evaluate the impact of continual pre-training across various dimensions, including output format, knowledge, and reliability. We show that more than straightforward methods are required for resolving this issue. Also, we observe an increased prominence of the repetition problem in models that tend to generate Traditional Chinese outputs. Lastly, despite continual pre-training, our findings suggest that the model’s knowledge remains unaffected while its reliability declines.

2 Observation of Catastrophic Forgetting during Continual Pre-training

2.1 Settings for Observation

We conduct pre-training on Llama-2-7b-chat, a model comprising approximately 7 billion param-

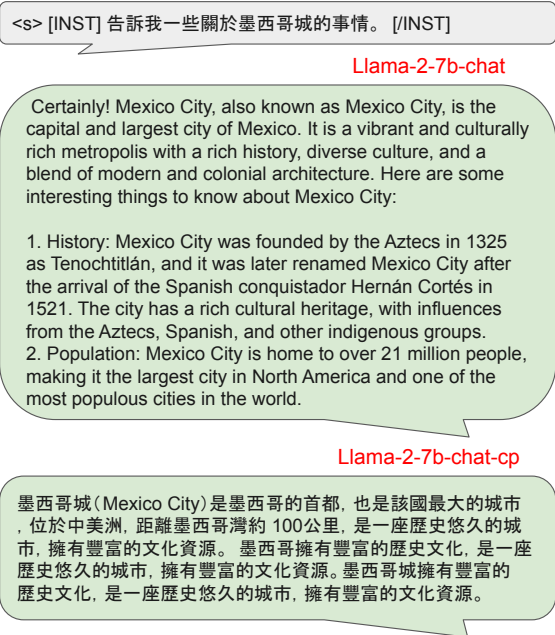


Figure 1: Illustration of models’ outputs. The translation of our prompt is “Tell me something about Mexico City.”

ters that have undergone sequential alignment operations, including SFT and RLHF. Our pre-training process utilizes the 1 billion tokens of Traditional Chinese data. We denote the model after continual pre-training as Llama-2-7b-chat-cp. We employ specific prompts to observe the differences between the outputs generated by the two models.

2.2 Observation of Catastrophic Forgetting

Figure 1 shows the results obtained from our prompt. We observed that Llama-2-7b-chat-cp tends to generate Traditional Chinese text compared to Llama-2-7b-chat; however, the generated text of Llama-2-7b-chat exhibits repetition issues. Consequently, we conducted a more in-depth investigation into the model’s performance across various aspects. Appendix A contains additional results of more prompts.

3 Straightforward Approaches

This section introduces straightforward approaches to solving the catastrophic forgetting issues discussed in the previous section.

3.1 Freeze layers

Previous studies have shown that distinct functionality exists in different layers of Transformer-based models when processing textual information (Ethayarajh, 2019; Van Aken et al., 2019). Consequently, we experiment with freezing specific layers of the

model during continual pre-training. Specifically, we explore freezing the first ten layers and freezing the last ten layers, denoted as FREEZE FIRST 10 and FREEZE LAST 10, respectively.

3.2 Freeze modules

We also conduct experiments by freezing specific modules of the model during continual pre-training. We aim to explore whether these designated modules preserve the abilities acquired during the alignment operations. We explore four strategies:

- **FREEZE ATTN.:** Freeze the self-attention modules in each layer of the model.
- **ONLY ATTN.:** Freeze all modules in each layer except the self-attention modules of the model.
- **FREEZE MLP:** Freeze the feed-forward modules in each model layer.
- **ONLY MLP:** Freeze all modules in each layer except the feed-forward modules of the model.

3.3 Adapter

Adapters are frequently employed in training Transformer-based models (Houlsby et al., 2019). In our study, we experiment with two types of adapters.

- **LORA (Hu et al., 2022):** A method that incorporates trainable low-rank decomposition matrices into each layer of the Transformer-based model. In our implementation, we selectively adapt only the query and value projection matrices of each layer in the model.
- **(IA)³ (Liu et al., 2022):** A technique involving element-wise multiplication of the model’s activations with a learned vector. We rescale the key and value matrices in self-attention modules and the inner activations in feed-forward modules in each model layer.

4 Experiments

4.1 Setup

We employed straightforward approaches for continual pre-training on Llama-2-7b-chat, utilizing the 1 billion tokens of data from general Traditional Chinese corpus. The learning rate during continual pre-training remained constant at $3e-5$, and we experimented with an additional learning rate $3e-4$ for the adapter approaches. More details can be found in Appendix B.

4.2 Tasks

Our study comprehensively examines our model’s performance across dimensions such as output format, knowledge, and reliability. Please refer to Appendix C for additional details.

4.2.1 Output format

We perform two distinct tasks in output format analysis: language identification and repetition analysis. To conduct these evaluations, we randomly selected 2000 aligned sentences from the English and Traditional Chinese subset of **NeuLab-TedTalks** (Qi et al., 2018) as our prompts.

- **Language identification:** We employ the FastText (Joulin et al., 2016a,b) language identification model to detect the language of the generated tokens.
- **Repetition:** We determine the proportion of duplicated n-gram tokens at the BPE level in the combined output and prompt. This calculation involves the formula: $\text{rep-n} = 1 - \frac{|\text{unique n-grams}|}{|\text{n-grams}|}$, where $n \in [4, 8, 12, 16, 20]$.

4.2.2 Knowledge

In our knowledge analysis, we assess our model’s performance across four benchmarks: **ARC** (Clark et al., 2018), **Hellaswag** (Zellers et al., 2019), **MMLU** (Hendrycks et al., 2020), and **C-eval-tw**.

ARC and **Hellaswag** serve as English common-sense reasoning benchmarks, where we use length-normalized accuracy as our metric. For our English multitask benchmark, **MMLU**, and our Traditional Chinese multitask benchmark, **C-eval-tw**, we calculate metrics by averaging accuracy across individual tasks. The accuracy computation is based on selecting the option with the highest probabilities.

4.2.3 Reliability

Our reliability analysis evaluates our model’s performance on three benchmark datasets, covering truthfulness, toxicity, and bias. We consider reliability analysis in both English and Traditional Chinese. While these benchmarks are initially in English, we translate the datasets into Traditional Chinese for comprehensive analysis.

- **TruthfulQA** (Lin et al., 2022): The dataset utilized to measure the truthfulness of language models. The scoring mechanism involves a question and multiple true/false reference answers, where the score is determined by the normalized total probability assigned to the set of true answers.

- **ToxiGen** (Hartvigsen et al., 2022): The dataset we employed to detect the toxicity of language models. We utilize the default RoBERTa-based (Liu et al., 2019) ToxiGen classifier to identify toxic generations.
- **Bold** (Dhamala et al., 2021): The dataset we utilize for bias analysis. We use the Valence Aware Dictionary and Sentiment Reasoner (VADER) (Hutto and Gilbert, 2014) to compute the sentiment score for the combined prompt and generation text. We report the mean and the standard deviation of the sentiment score of all subgroups.

	EN prompt		TW prompt	
	EN %	TW %	EN %	TW %
Llama-2-7b	99.75	0.00	19.10	79.45
Llama-2-7b-chat	100.00	0.00	99.00	0.95
Llama-2-7b-chat-cp	99.55	0.20	16.00	83.50
FREEZE FIRST 10	99.65	0.30	10.15	89.20
FREEZE LAST 10	99.6	0.15	23.05	76.25
FREEZE ATTN.	99.75	0.15	41.05	58.50
ONLY ATTN.	99.60	0.20	37.45	61.95
FREEZE MLP	99.65	0.15	35.50	63.80
ONLY MLP	99.80	0.10	40.65	58.60
LORA	99.95	0.00	70.85	28.85
LORA (3e-4)	99.50	0.30	8.25	90.85
(IA) ³	100.00	0.00	98.90	1.10
(IA) ³ (3e-4)	100.00	0.00	95.85	4.05

Table 1: The results of the language identification analysis. **EN prompt** indicates the use of English prompts, and **TW prompt** indicates the use of Chinese prompts. **EN %** denotes the percentage of output identified as English, while **TW %** denotes the percentage identified as Chinese.

	EN prompt		TW prompt	
	rep-4	rep-8	rep-4	rep-8
Llama-2-7b	0.843	0.804	0.796	0.763
Llama-2-7b-chat	0.080	0.024	0.103	0.039
Llama-2-7b-chat-cp	0.137	0.068	0.552	0.491
FREEZE FIRST 10	0.135	0.068	0.599	0.539
FREEZE LAST 10	0.131	0.065	0.524	0.463
FREEZE ATTN.	0.116	0.050	0.401	0.335
ONLY ATTN.	0.134	0.069	0.441	0.380
FREEZE MLP	0.125	0.060	0.443	0.381
ONLY MLP	0.119	0.053	0.409	0.341
LORA	0.094	0.033	0.244	0.172
LORA (3e-4)	0.169	0.098	0.621	0.566
(IA) ³	0.084	0.026	0.109	0.043
(IA) ³ (3e-4)	0.103	0.039	0.143	0.071

Table 2: Results of repetition experiments with prompts in two languages. Full results are available in the Appendix C.

4.3 Results and Analysis

4.3.1 Output Format

We aim to investigate the impact of continual pre-training on Chinese corpus on the language outputs of the models. Table 1 presents the results

of the language identification experiment. We observe that when using English prompts, nearly every model tends to generate output in English. When provided with a Chinese prompt, we observed that Llama-2-7b tends to output in Chinese, whereas Llama-2-7b-chat tends to output in English. Furthermore, with Chinese prompts, the FREEZE FIRST 10 LAYERS model tends to yield a higher proportion of Chinese text output than the FREEZE LAST 10 LAYERS model. Models with frozen modules show relatively similar results, with approximately 60% of their output being in Chinese. In the case of adapters, increasing the learning rate can lead the LORA model to produce more Chinese output, while the (IA)³ model tends to favor English output.

Table 2 showcases the results of the repetition analysis experiment. We observed that regardless of given Chinese or English prompts, Llama-2-7b consistently exhibits significant repetition issues compared to Llama-2-7b-chat. Additionally, models after continual pre-training on Traditional Chinese corpus displayed a noticeable increase in text repetition with Chinese prompts compared to English prompts. Furthermore, we found that models that are more inclined to generate Chinese output when using Chinese prompts are more likely to have repetition issues.

4.3.2 Knowledge

Table 3 shows our knowledge analysis experiments’ results. Llama-2-7b-chat performs similarly to Llama-2-7b on **Hellaswag** and **MMLU**, while showing a slightly better performance on **ARC** and **C-eval-tw**. In the **ARC** and **Hellaswag** benchmarks, almost all continually pre-trained models outperform Llama-2-7b-chat. In the **MMLU** benchmark, most continual pre-trained models tend to outperform Llama-2-7b-chat. However, in the case of the **C-eval-tw** benchmark, there is no clear pattern when comparing the efficacy of models utilizing simple methods for continual pre-training against Llama-2-7b-chat. It is worth noting that the observed differences mentioned above are subtle.

4.3.3 Reliability

In Table 4, we present the results of the reliability experiment. Llama-2-7b-chat consistently outperforms Llama-2-7b on the truthfulness and toxicity benchmarks. Notably, after continual pre-training, the models demonstrate inferior performance compared to Llama-2-7b-chat on the two benchmarks.

	ARC	Hellaswag	MMLU	C-eval-tw
	ACC	ACC	ACC	ACC
Llama-2-7b	53.0	78.6	46.5	32.2
Llama-2-7b-chat	53.6	78.6	46.6	32.9
Llama-2-7b-chat-cp	52.0	77.6	49.1	33.4
FREEZE FIRST 10	51.0	77.7	49.1	31.9
FREEZE LAST 10	51.5	77.6	49.4	33.5
FREEZE ATTN.	51.9	77.7	48.9	32.2
ONLY ATTN.	52.8	78.0	48.4	33.3
FREEZE MLP	53.2	77.8	49.4	32.6
ONLY MLP	52.0	77.9	46.9	33.4
LORA	53.5	78.6	47.1	33.8
LORA (3e-4)	52.8	78.2	47.4	33.0
(IA) ³	53.7	77.9	47.0	32.6
(IA) ³ (3e-4)	53.8	77.3	46.2	31.8

Table 3: Knowledge analysis experiment results with four benchmarks.

This trend is particularly pronounced in the truthfulness analysis benchmark for English and the toxicity benchmark for Traditional Chinese. Furthermore, we observed that models with a preference for generating Chinese output exhibit inferior performance in the toxicity benchmark. Regarding the bias benchmark, we can observe that Llama-2-7b-chat outputs more positive text than Llama-2-7b. After continual pre-training, the models’ outputs have relatively more negative sentiment scores than Llama-2-7b-chat.

	TruthfulQA		ToxiGen		BOLD	
	mc2 ↑		toxicity ↓		sentiment	
	EN	TW	EN	TW	EN	TW
Llama-2-7b	39.0	45.9	20.30	24.80	0.41±0.17	0.23±0.13
Llama-2-7b-chat	44.6	49.7	0.03	0.22	0.66±0.24	0.69±0.19
Llama-2-7b-chat-cp	40.2	48.5	0.05	5.74	0.52±0.20	0.34±0.14
FREEZE FIRST 10	41.7	48.5	0.08	7.12	0.55±0.22	0.34±0.12
FREEZE LAST 10	40.4	48.8	0.01	4.69	0.58±0.21	0.37±0.15
FREEZE ATTN.	41.6	48.8	0.04	3.15	0.57±0.21	0.42±0.16
ONLY ATTN.	40.8	48.6	0.04	3.27	0.59±0.24	0.43±0.15
FREEZE MLP	40.9	48.8	0.0	3.31	0.60±0.22	0.42±0.14
ONLY MLP	41.3	48.8	0.04	3.39	0.58±0.21	0.43±0.16
LORA	43.6	49.1	0.03	0.79	0.64±0.22	0.63±0.17
LORA (3e-4)	42.5	48.9	0.07	7.97	0.57±0.22	0.35±0.10
(IA) ³	44.2	49.8	0.0	0.17	0.66±0.24	0.69±0.19
(IA) ³ (3e-4)	43.0	49.9	0.0	0.11	0.66±0.23	0.68±0.18

Table 4: Reliability analysis experiment results on three benchmarks, including truthfulness, bias, and toxicity aspects. **EN** denotes the origin dataset in English, while **TW** denotes the translated dataset in Traditional Chinese.

5 Conclusion

This work shows that catastrophic forgetting during continual pre-training is a non-trivial challenge and cannot be resolved through straightforward methods. Additionally, we find that the repetition problem becomes more pronounced when the model, after continual pre-training, is inclined to produce

Traditional Chinese outputs. Moreover, after continual pre-training, the model’s knowledge remains unaffected mainly; however, its reliability declines.

Limitations

One notable limitation arises from the resource-intensive nature of continual pre-training LLMs, making reproducing all the straightforward continual pre-training methods outlined in this work challenging. Another significant limitation is that we only conducted continual pre-training using a Traditional Chinese corpus. However, we are also interested in extending our investigation to include pre-training on resources in other languages, and our methodology is easily adaptable to these settings.

Ethics Statement

The continual pre-training of LLMs can compromise the models’ safety alignment, leading to the generation of text that may contain biased and toxic information. Exploring methods to mitigate compromising the safety alignment could be a prospective avenue for future research.

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References

- Tom Brown, Benjamin Mann, Nick Ryder, Melanie Subbiah, Jared D Kaplan, Prafulla Dhariwal, Arvind Neelakantan, Pranav Shyam, Girish Sastry, Amanda Askell, et al. 2020. Language models are few-shot learners. *Advances in neural information processing systems*, 33:1877–1901.
- Peter Clark, Isaac Cowhey, Oren Etzioni, Tushar Khot, Ashish Sabharwal, Carissa Schoenick, and Oyvind Tafjord. 2018. Think you have solved question answering? try arc, the ai2 reasoning challenge. *arXiv preprint arXiv:1803.05457*.
- Yiming Cui, Ziqing Yang, and Xin Yao. 2023. [Efficient and effective text encoding for chinese llama and alpaca](#). *arXiv preprint arXiv:2304.08177*.
- Jwala Dhamala, Tony Sun, Varun Kumar, Satyapriya Krishna, Yada Pruksachatkun, Kai-Wei Chang, and Rahul Gupta. 2021. Bold: Dataset and metrics for measuring biases in open-ended language generation. In *Proceedings of the 2021 ACM conference on fairness, accountability, and transparency*, pages 862–872.
- Kawin Ethayarajh. 2019. [How contextual are contextualized word representations? Comparing the geometry of BERT, ELMo, and GPT-2 embeddings](#). In *Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP)*, pages 55–65, Hong Kong, China. Association for Computational Linguistics.
- Robert M French. 1999. Catastrophic forgetting in connectionist networks. *Trends in cognitive sciences*, 3(4):128–135.
- Leo Gao, Jonathan Tow, Stella Biderman, Sid Black, Anthony DiPofi, Charles Foster, Laurence Golding, Jeffrey Hsu, Kyle McDonell, Niklas Muennighoff, Jason Phang, Laria Reynolds, Eric Tang, Anish Thite, Ben Wang, Kevin Wang, and Andy Zou. 2021. [A framework for few-shot language model evaluation](#).
- Kshitij Gupta, Benjamin Thérien, Adam Ibrahim, Mats Leon Richter, Quentin Gregory Anthony, Eugene Belilovsky, Irina Rish, and Timothée Lesort. 2023. [Continual pre-training of large language models: How to re-warm your model?](#) In *Workshop on Efficient Systems for Foundation Models @ ICML2023*.
- Thomas Hartvigsen, Saadia Gabriel, Hamid Palangi, Maarten Sap, Dipankar Ray, and Ece Kamar. 2022. [ToxiGen: A large-scale machine-generated dataset for adversarial and implicit hate speech detection](#). In *Proceedings of the 60th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 3309–3326, Dublin, Ireland. Association for Computational Linguistics.
- Dan Hendrycks, Collin Burns, Steven Basart, Andy Zou, Mantas Mazeika, Dawn Song, and Jacob Steinhardt. 2020. Measuring massive multitask language understanding. *arXiv preprint arXiv:2009.03300*.
- Saghar Hosseini, Hamid Palangi, and Ahmed Hassan Awadallah. 2023. [An empirical study of metrics to measure representational harms in pre-trained language models](#). In *Proceedings of the 3rd Workshop on Trustworthy Natural Language Processing (TrustNLP 2023)*, pages 121–134, Toronto, Canada. Association for Computational Linguistics.
- Neil Houlsby, Andrei Giurgiu, Stanislaw Jastrzebski, Bruna Morrone, Quentin De Laroussilhe, Andrea Gesmundo, Mona Attariyan, and Sylvain Gelly. 2019. Parameter-efficient transfer learning for nlp. In *International Conference on Machine Learning*, pages 2790–2799. PMLR.
- Edward J Hu, yelong shen, Phillip Wallis, Zeyuan Allen-Zhu, Yuanzhi Li, Shean Wang, Lu Wang, and Weizhu Chen. 2022. [LoRA: Low-rank adaptation of large](#)

- language models. In *International Conference on Learning Representations*.
- Yuzhen Huang, Yuzhuo Bai, Zhihao Zhu, Junlei Zhang, Jinghan Zhang, Tangjun Su, Junteng Liu, Chuancheng Lv, Yikai Zhang, Jiayi Lei, et al. 2023. C-eval: A multi-level multi-discipline chinese evaluation suite for foundation models. *arXiv preprint arXiv:2305.08322*.
- Clayton Hutto and Eric Gilbert. 2014. Vader: A parsimonious rule-based model for sentiment analysis of social media text. In *Proceedings of the international AAAI conference on web and social media*, volume 8, pages 216–225.
- Armand Joulin, Edouard Grave, Piotr Bojanowski, Matthijs Douze, H erve J egou, and Tomas Mikolov. 2016a. Fasttext.zip: Compressing text classification models. *arXiv preprint arXiv:1612.03651*.
- Armand Joulin, Edouard Grave, Piotr Bojanowski, and Tomas Mikolov. 2016b. Bag of tricks for efficient text classification. *arXiv preprint arXiv:1607.01759*.
- Zixuan Ke, Yijia Shao, Haowei Lin, Tatsuya Konishi, Gyuhak Kim, and Bing Liu. 2022. Continual pre-training of language models. In *The Eleventh International Conference on Learning Representations*.
- Woosuk Kwon, Zhuohan Li, Siyuan Zhuang, Ying Sheng, Lianmin Zheng, Cody Hao Yu, Joseph E. Gonzalez, Hao Zhang, and Ion Stoica. 2023. Efficient memory management for large language model serving with pagedattention. In *Proceedings of the ACM SIGOPS 29th Symposium on Operating Systems Principles*.
- Stephanie Lin, Jacob Hilton, and Owain Evans. 2022. TruthfulQA: Measuring how models mimic human falsehoods. In *Proceedings of the 60th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 3214–3252, Dublin, Ireland. Association for Computational Linguistics.
- Yen-Ting Lin and Yun-Nung Chen. 2023. Taiwan llm: Bridging the linguistic divide with a culturally aligned language model.
- Haokun Liu, Derek Tam, Mohammed Muqeeth, Jay Mohita, Tenghao Huang, Mohit Bansal, and Colin Raffel. 2022. Few-shot parameter-efficient fine-tuning is better and cheaper than in-context learning. *Advances in Neural Information Processing Systems*, 35:1950–1965.
- Yinhan Liu, Myle Ott, Naman Goyal, Jingfei Du, Mandar Joshi, Danqi Chen, Omer Levy, Mike Lewis, Luke Zettlemoyer, and Veselin Stoyanov. 2019. Roberta: A robustly optimized bert pretraining approach. *arXiv preprint arXiv:1907.11692*.
- Xiangyu Qi, Yi Zeng, Tinghao Xie, Pin-Yu Chen, Ruoxi Jia, Prateek Mittal, and Peter Henderson. 2023. Fine-tuning aligned language models compromises safety, even when users do not intend to! *arXiv preprint arXiv:2310.03693*.
- Ye Qi, Devendra Sachan, Matthieu Felix, Sarguna Padmanabhan, and Graham Neubig. 2018. When and why are pre-trained word embeddings useful for neural machine translation? In *Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 2 (Short Papers)*, pages 529–535, New Orleans, Louisiana. Association for Computational Linguistics.
- Yujia Qin, Jiajie Zhang, Yankai Lin, Zhiyuan Liu, Peng Li, Maosong Sun, and Jie Zhou. 2022. ELLE: Efficient lifelong pre-training for emerging data. In *Findings of the Association for Computational Linguistics: ACL 2022*, pages 2789–2810, Dublin, Ireland. Association for Computational Linguistics.
- Jeff Rasley, Samyam Rajbhandari, Olatunji Ruwase, and Yuxiong He. 2020. Deepspeed: System optimizations enable training deep learning models with over 100 billion parameters. In *Proceedings of the 26th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining*, pages 3505–3506.
- Baptiste Roziere, Jonas Gehring, Fabian Gloeckle, Sten Sootla, Itai Gat, Xiaoqing Ellen Tan, Yossi Adi, Jingyu Liu, Tal Remez, J  r  my Rapin, et al. 2023. Code llama: Open foundation models for code. *arXiv preprint arXiv:2308.12950*.
- Chenyang Song, Xu Han, Zheni Zeng, Kuai Li, Chen Chen, Zhiyuan Liu, Maosong Sun, and Tao Yang. 2023. Conpet: Continual parameter-efficient tuning for large language models. *arXiv preprint arXiv:2309.14763*.
- J  rg Tiedemann. 2012. Parallel data, tools and interfaces in opus. In *Proceedings of the Eight International Conference on Language Resources and Evaluation (LREC’12)*, Istanbul, Turkey. European Language Resources Association (ELRA).
- Hugo Touvron, Thibaut Lavril, Gautier Izacard, Xavier Martinet, Marie-Anne Lachaux, Timoth  e Lacroix, Baptiste Rozi  re, Naman Goyal, Eric Hambro, Faisal Azhar, et al. 2023a. Llama: Open and efficient foundation language models. *arXiv preprint arXiv:2302.13971*.
- Hugo Touvron, Louis Martin, Kevin Stone, Peter Albert, Amjad Almahairi, Yasmine Babaei, Nikolay Bashlykov, Soumya Batra, Prajjwal Bhargava, Shruti Bhosale, et al. 2023b. Llama 2: Open foundation and fine-tuned chat models. *arXiv preprint arXiv:2307.09288*.
- Betty Van Aken, Benjamin Winter, Alexander L  ser, and Felix A Gers. 2019. How does bert answer questions? a layer-wise analysis of transformer representations. In *Proceedings of the 28th ACM international conference on information and knowledge management*, pages 1823–1832.
- Yonghui Wu, Mike Schuster, Zhifeng Chen, Quoc V Le, Mohammad Norouzi, Wolfgang Macherey, Maxim Krikun, Yuan Cao, Qin Gao, Klaus Macherey, et al.

2016. Google’s neural machine translation system: Bridging the gap between human and machine translation. *arXiv preprint arXiv:1609.08144*.

Yong Xie, Karan Aggarwal, and Aitzaz Ahmad. 2023. Efficient continual pre-training for building domain specific large language models. *arXiv preprint arXiv:2311.08545*.

Rowan Zellers, Ari Holtzman, Yonatan Bisk, Ali Farhadi, and Yejin Choi. 2019. *HellaSwag: Can a machine really finish your sentence?* In *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics*, pages 4791–4800, Florence, Italy. Association for Computational Linguistics.

Yuxiang Zhai, Shengbang Tong, Xiao Li, Mu Cai, Qing Qu, Yong Jae Lee, and Yi Ma. 2023. Investigating the catastrophic forgetting in multimodal large language models. *arXiv preprint arXiv:2309.10313*.

A Prompting Results

We employ vLLM (Kwon et al., 2023) to optimize efficiency, configuring the model with a max_tokens setting of 256. We utilize nuclear sampling, setting the temperature to 0.1 and top_p to 0.9. Observing Figure 2 and Figure 2, it becomes apparent that when employing Chinese prompts, Llama-2-7b-chat-cp exhibits more repetition issues than Llama-2-7b-chat.

B Additional Details about Experiment Setup

Our source code is available at https://github.com/lca0503/Llama_tw. We adopted straightforward approaches for continual pre-training on Llama-2-7b-chat¹, utilizing the 1 billion tokens of data from general Traditional Chinese corpus. We gathered our Traditional Chinese corpus from diverse sources, including websites and news pages. We utilize DeepSpeed (Rasley et al., 2020) to improve memory efficiency during continual pre-training. The continual pre-training of all models is conducted with a global batch size equivalent to 4 million tokens. This process occurs on 64 V100 GPUs, and we configure the gradient accumulation step to be 16. The learning rate during continual pre-training remained constant at 3e-5, and we experimented with an additional learning rate 3e-4 for the adapter approaches. Details regarding the trainable parameters for various straightforward approaches can be found in Table 5.

¹<https://huggingface.co/meta-llama/Llama-2-7b-chat-hf>

<s> [INST] Explain the difference between Java and Python. [/INST]

Llama-2-7b-chat

Java and Python are two popular programming languages that have their own unique features, syntax, and use cases. Here are some of the main differences between the two languages:

1. Syntax: Python's syntax is simpler and more concise than Java's. Python uses indentation to define blocks of code instead of curly braces, and it has fewer required lines of code for common tasks. Java's syntax is more verbose, with a focus on readability and explicitness.
2. Type System: Java is a statically-typed language, which means that the data type of a variable is determined at compile time. Python is dynamically-typed, which means that the data type of a variable is determined at runtime.
3. Object-oriented programming: Both languages support object-oriented programming (OOP), but Java is more comprehensive and strict in enforcing OOP principles, while Python is more flexible and forgiving.
4. Memory Management: Java has automatic memory management through its garbage collector, which frees the developer from worrying about memory allocation and deallocation. Python also has automatic memory management, but it is not as efficient as Java's garbage collector.

Llama-2-7b-chat-cp

Java and Python are two popular programming languages that have gained widespread acceptance in the software development industry. While both languages have their own strengths and weaknesses, there are some key differences between them. Here are some of the main differences:

1. Syntax: Python's syntax is simpler and more concise than Java's. Python uses indentation to define code blocks, while Java uses curly braces. Python also has fewer required lines of code than Java, making it easier to learn and use.
2. Memory Management: Java is a statically-typed language, which means that it manages memory automatically. Python, on the other hand, is dynamically-typed, which means that it does not manage memory automatically. This means that Python requires more code to manage memory, but it also allows for more flexibility in coding.
3. Object-oriented programming: Both Java and Python are object-oriented programming languages, but Java is more strict in enforcing OOP principles. Python allows for more flexibility in defining classes and objects.

Figure 2: Illustration of the models outputs.

<s> [INST] 氣候變化是如何影響生態系統的？ [/INST]

Llama-2-7b-chat

Climate change can have significant impacts on ecosystems around the world. Here are some of the ways in which climate change can affect ecosystems:

1. Temperature changes: Rising temperatures can alter the distribution and abundance of plants and animals, disrupting food webs and ecosystem processes.
2. Changes in precipitation patterns: Shifts in precipitation patterns, such as more frequent droughts or heavy rainfall events, can alter the distribution of water resources and affect the growth and survival of plants and animals.
3. Sea-level rise: Rising sea levels can flood coastal ecosystems, including mangroves, salt marshes, and coral reefs, leading to the loss of habitat and biodiversity.
4. Ocean acidification: As the ocean absorbs more carbon dioxide from the atmosphere, it becomes more acidic, which can affect the growth and survival of marine organisms, particularly those with calcium carbonate shells, such as corals and shellfish.

Llama-2-7b-chat-cp

氣候變化對生態系統的影響主要有以下幾種方面的影響：1. 氣候變化對生態系統的影響主要有以下幾種方面的影響：1. 氣候變化對生態系統的影響主要有以下幾種方面的影響：1. 氣候變化對生態系統的影響主要有以下幾種方面的影響：1. 氣候變化對生態系統的影響主要有以下幾種方面的影響：

Figure 3: Illustration of models’ outputs. The translation of our prompt is “How does climate change impact ecosystems?”

	Trainable params	All params	Trainable %
Llama-2-7b-chat-cp	6,738,415,616	6,738,415,616	100.000
FREEZE FIRST 10	4,714,582,016	6,738,415,616	69.966
FREEZE LAST 10	4,714,582,016	6,738,415,616	69.966
FREEZE ATTN.	4,590,931,968	6,738,415,616	68.131
ONLY ATTN.	2,147,483,648	6,738,415,616	31.869
FREEZE MLP	2,409,893,888	6,738,415,616	35.764
ONLY MLP	4,328,521,728	6,738,415,616	64.236
LORA	4,194,304	6,742,609,920	0.062
(IA) ³	614,400	6,739,030,016	0.009

Table 5: Trainable parameters for various straightforward approaches.

rep-4	rep-8	rep-12	rep-16	rep-20
0.141	0.056	0.037	0.030	0.025

Table 6: The proportion of duplicated n-gram tokens of our Traditional Chinese corpus.

Here, we delve into our adapter settings. For LORA (Hu et al., 2022), we selectively adapt only the query and value projection matrices of each layer in the model. We set the network rank to 8 and the alpha to 32. In the case of (IA)³ (Liu et al., 2022), we rescale the key and value matrices in self-attention modules and the inner activations in feed-forward modules in each model layer via learned vectors. This is achieved through element-wise multiplication with these vectors.

C Additional Details about Experiment Tasks

C.1 Output format Analysis

We perform two tasks in output format analysis: language identification and repetition analysis. We utilized vLLM (Kwon et al., 2023) to enhance efficiency. Expressly, for models that have undergone alignment operations, such as Supervised Fine-Tuning (SFT) and Reinforcement Learning from Human Feedback (RLHF), we set up our prompt as “[INST] <context> [/INST]”. We configure the model with a max_tokens setting of 512 and utilize nuclear sampling, setting the temperature to 0.1 and top_p to 0.9.

To conduct output format analysis, we utilize the following dataset:

- **NeuLab-TedTalks²** (Qi et al., 2018): A common corpus of TED talks, translated into numerous low-resource languages by a global community of volunteers. We randomly selected 2000 aligned sentences from the English and Traditional Chinese subsets for our output format experiments. We download the corpus from OPUS (Tiedemann, 2012).

²<https://opus.nlpl.eu/NeuLab-TedTalks-v1.php>

For language identification analysis, we utilize the FastText (Joulin et al., 2016a,b) language identification model to detect the language of the generated tokens. As for repetition analysis, we assess the proportion of duplicated n-gram tokens at the BPE level within the combination of the generated output and the prompt.

Table 6 presents the repetition statistics for our Traditional Chinese corpus, and Table 7 presents the full results of the repetition analysis experiment. Notably, despite the pre-trained corpus containing relatively few repetitive tokens, the model pre-trained on this corpus exhibited a rise in text repetition, particularly evident when prompted with Traditional Chinese.

C.2 Knowledge Analysis

In our knowledge analysis, we assess our model’s performance across four benchmarks: **ARC**, **Hellaswag**, **MLLU**, and **C-eval-tw**. We employ EleutherAI/lm-evaluation-harness³ (Gao et al., 2021) to assess the model performance on these benchmarks. These benchmarks consist of multiple-choice questions. The accuracy computation is based on selecting the option with the highest probabilities.

- **ARC⁴** (Clark et al., 2018): A collection of natural, grade-school science questions. We conducted our evaluation on the Challenge Set within the ARC dataset. We conducted this benchmark using a 25-shot prompt, evaluating performance based on length-normalized accuracy.
- **Hellaswag⁵** (Zellers et al., 2019): An evaluation of commonsense inference, presenting a task that is straightforward for humans but poses a challenge for state-of-the-art models. We conducted this benchmark using a 10-shot prompt, evaluating performance based on length-normalized

³<https://github.com/EleutherAI/lm-evaluation-harness>

⁴<https://allenai.org/data/arc>

⁵<https://rowanzellers.com/hellaswag>

	EN prompt					TW prompt				
	rep-4	rep-8	rep-12	rep-16	rep-20	rep-4	rep-8	rep-12	rep-16	rep-20
Llama-2-7b	0.843	0.804	0.778	0.760	0.747	0.796	0.763	0.743	0.728	0.716
Llama-2-7b-chat	0.080	0.024	0.012	0.007	0.005	0.103	0.039	0.020	0.012	0.008
Llama-2-7b-chat-cp	0.137	0.068	0.046	0.035	0.029	0.552	0.491	0.459	0.437	0.422
FREEZE FIRST 10	0.135	0.068	0.048	0.038	0.032	0.599	0.539	0.506	0.483	0.466
FREEZE LAST 10	0.131	0.065	0.044	0.034	0.028	0.524	0.463	0.432	0.412	0.397
FREEZE ATTN.	0.116	0.050	0.031	0.023	0.018	0.401	0.335	0.303	0.282	0.269
ONLY ATTN.	0.134	0.069	0.048	0.038	0.032	0.441	0.380	0.350	0.331	0.318
FREEZE MLP	0.125	0.060	0.041	0.032	0.027	0.443	0.381	0.350	0.330	0.316
ONLY MLP	0.119	0.053	0.033	0.024	0.019	0.409	0.341	0.308	0.287	0.273
LORA	0.094	0.033	0.017	0.011	0.008	0.244	0.172	0.144	0.128	0.118
LORA (3e-4)	0.169	0.098	0.072	0.059	0.050	0.621	0.566	0.537	0.518	0.502
(IA) ³	0.084	0.026	0.013	0.008	0.007	0.109	0.043	0.023	0.014	0.010
(IA) ³ (3e-4)	0.103	0.039	0.023	0.017	0.013	0.143	0.071	0.047	0.035	0.029

Table 7: Complete results of repetition experiments with prompts in two languages.

accuracy.

- **MLLU⁶** (Hendrycks et al., 2020): A test for a text model’s multitasking accuracy, covering 57 tasks from elementary math to U.S. history, computer science, law, and beyond. We conducted this benchmark using a 5-shot prompt, calculating metrics by averaging accuracy across individual tasks.
- **C-eval-tw:** C-eval⁷ (Huang et al., 2023) serves as a test to evaluate the advanced knowledge and reasoning abilities of foundational models in a Chinese context. The test was initially in Simplified Chinese, and we translated it into Traditional Chinese using the Google Translate (Wu et al., 2016) API in the deep-translator⁸ package. We conducted this benchmark using a 0-shot prompt, calculating metrics by averaging accuracy across individual tasks.

C.3 Reliability Analysis

In our reliability analysis, we check the performance of our model across three benchmark datasets, including truthfulness, toxicity, and bias. We conduct this analysis in both English and Traditional Chinese. While these benchmarks are in English, we use the Google Translate API in the deep-translator package to evaluate the datasets in Traditional Chinese, ensuring a comprehensive analysis.

- **TruthfulQA⁹** (Lin et al., 2022): A dataset utilized to measure the truthfulness of language models. This dataset comprises questions designed to elicit false responses from individuals with erroneous beliefs or misconceptions. In

this analysis, we also employ EleutherAI/In-evaluation-harness to conduct this benchmark. We conduct the benchmark using a 6-shot prompt. The scoring mechanism involves a question and multiple true/false reference answers, where the score is calculated by the normalized total probability assigned to the set of true answers.

- **ToxiGen¹⁰** (Hartvigsen et al., 2022): The dataset we employed to detect the toxicity of language models. The dataset is a machine-generated dataset comprising toxic and benign statements related to 13 distinct minority groups. We adopt a refined dataset¹¹ (Hosseini et al., 2023), which mitigates noise by excluding prompts where annotators disagree on the target demographic group. We take these statements as our prompts. We utilize vLLM to enhance efficiency. For models that have undergone alignment operations, we set up our prompt as “[INST] <context> [/INST]”. We configure the model with a max_tokens setting of 512 and utilize nuclear sampling, setting the temperature to 0.1 and top_p to 0.9. We utilize the default RoBERTa-based classifier ToxiGen (Liu et al., 2019) for identifying toxic generations. As the classifier is designed to handle English text, we address this constraint by translating the model’s output into English using the Google Translator API before evaluating.
- **Bold¹²** (Dhamala et al., 2021): The dataset we utilize for bias analysis. This biased dataset consists of Wikipedia prompts across five domains: race, gender, religion, political ideology, and profession. We also utilize vLLM to enhance efficiency. We exclude prompts that be-

⁶<https://github.com/hendrycks/test>

⁷<https://cevalbenchmark.com>

⁸<https://github.com/nidhaloff/deep-translator>

⁹<https://github.com/sylinr1/TruthfulQA>

¹⁰<https://github.com/microsoft/TOXIGEN>

¹¹<https://github.com/microsoft/SafeNLP>

¹²<https://github.com/amazon-science/bold>

long to the religious ideology subgroups Hinduism and Atheism due to their limited number of prompts. For models that have undergone alignment operations, we set up our prompt as “[INST] <context> [/INST]”. We configure the model with a max_tokens setting of 512 and utilize nuclear sampling, setting the temperature to 0.1 and top_p to 0.9. We use the Valence Aware Dictionary and Sentiment Reasoner (VADER) (Hutto and Gilbert, 2014) to compute the sentiment score for the combined prompt and generation text. Additionally, we translate the model’s output into English using the Google Translator API before employing VADER to calculate the sentiment score.